SEQUENTIAL FUSION OF DECISIONS WITH FAVOURABLE DEPENDENCE FOR CONTROLLED VERIFICATION ERRORS

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ABSTRACT

Statistical dependence between classifier decisions is often shown to improve performance over statistically independent decisions. Though the solution for favourable dependence between two classifier decisions has been derived, the theoretical analysis for the general case of 'n' client and impostor decision fusion has not been presented before. This paper presents the expressions developed for favourable dependence of multi-instance and multi-sample fusion schemes that employ 'AND' and 'OR' rules. The expressions are experimentally evaluated by considering the proposed architecture for text-dependent speaker verification using HMM based digit dependent speaker models. The improvement in fusion performance is found to be higher when digit combinations with favourable client and impostor decisions are used for speaker verification. The total error rate of 20% for fusion of independent decisions is reduced to 2.1% for fusion of decisions that are favourable for both client and impostors. The expressions developed here are also applicable to other biometric modalities, such as finger prints and handwriting samples, for reliable identity verification.

1. INTRODUCTION

Fusion techniques have received considerable attention for achieving lower verification error rates with biometrics. The performance of a fused verification system is dependent on the base classifier performances and the correlation between the classifiers [1]. Many researchers have investigated whether fusion of independent classifiers results in better performance than fusion of dependent classifiers [2, 3]. Although the assumption of statistical independence often appears to be unrealistic, the assumption holds for some applications in multi-modal biometric fusion [4]. The incorporation of correlation into fusion has been shown to have significant improvement in performance than a fusion scheme based on the statistical independence assumption [5-8].

The assumption of independence can often provide an adequate and workable approximation of the reality which may be more complex. Expressions have been previously derived for a multi-instance and multi-sample fusion method [9] under the assumption of statistical independence between the classifier decisions for controlled trade-off between false rejection rate (FRR) and false acceptance rate (FAR). The analysis is further extended to consider the modeling of correlation between classifier decisions [10]. In this work, favourable dependence between classifier decisions has been shown to improve the performance of the proposed fusion scheme. However, the complete theoretical and empirical analysis to identity the conditions for favourable dependence for '*n*'th order correlation coefficients has not been presented before [8, 10].

The dependence relationship, measured using Q-statistic, between two classifier decisions for OR fusion [7] is negative for favourable authentic decisions and positive for favourable impostor decisions. For 'AND' fusion [6], the positive Q-statistic for authentic decisions and negative Q-statistic for impostor decisions are favourable. But a complete analysis for determining the conditional dependence between classifiers more than two has not been fully explored [8]. This work presents the expressions developed for determining the favourable dependence of decisions from '*n*' instances and '*m*' samples using 'AND' and 'OR' rules. These expressions enable the determination of the combinations with favourable dependence that improve the performance of a multi-instance and multi-sample fusion architecture [10].

Section 2 and section 3 presents the theoretical analysis for favourable dependence of multi-instance and multi-sample fusion schemes respectively. The next section develops the expressions of dependence for integration of these two fusion schemes. The paper also presents the methodology (section 5) used for the evaluation (section 6) of these derived expressions in the context of text-dependent speaker verification.

2. FUSION OF CORRELATED DECISIONS FROM MULTIPLE INSTANCES

The dependence between the classifier decisions is estimated based on the Bahadur-Lazarsfeld Expansion (BLE) [10]. The expansion begins with the calculation of ideal error rates that are multiplied with a correction factor. The expressions for ideal error rates of multi-instance fusion schemes [9] can be given as

$$p^0_{Ideal} = \alpha_1\alpha_2\alpha_3...\alpha_n \ \left(\alpha_i = FAR_i \text{ for instance } i\right) \quad (1)$$

$$\rho^1_{Ideal} = \beta_1\beta_2\beta_3...\beta_n \left(\beta_i = (1-FRR_i) \text{ for instance } i\right) \quad (2)$$

Here ideal refers to the case of statistically independent decisions. Superscript '0' refers to FAR and '1' to FRR. whereas subscripts identify the multiple instances in equations (1) & (2). α's and β's are the base classifier FAR and (1-FRR). The equations to calculate the error rates for multi-instance fusion *with incorporation of correlation* between the decisions can be given [11] as

$$p^a_E = p^a_{Ideal}\left(1 + \sum_{i<j}\gamma^a_{ij} z^a_i z^a_j + \sum_{i<j<k}\gamma^a_{ijk} z^a_i z^a_j z^a_k + ...\right) \quad (3)$$

$$\text{where } \gamma^a_{123...n} = E\left[z^a_1 z^a_2 ....z^a_n\right] \quad (4)$$

$$\text{and } z^0_i = \frac{d_i - \alpha_i}{\sqrt{\alpha_i(1-\alpha_i)}}, \ z^1_i = \frac{d_i - \beta_i}{\sqrt{\beta_i(1-\beta_i)}} \quad (5)$$

Here $\gamma^a (a = 0,1)$ are the correlation coefficients for client & impostor decisions. They are defined using z_i variables that are orthogonal with respect to the independence model with zero mean and unit variance. Decisions d_i are 1 for client & 0 for impostors and so z_i^0 are positive for incorrect impostor decisions and negative for correct ones. If two classifiers are such that one is correct when the other is not and vice versa most of the time, these variables can contribute to negative correlation thereby resulting favourable dependence. Client decisions are similarly handled with z_i^1. The magnitude and sign of the correlation, however, depend on the summation over all combinations. The expansion continues to third and higher order decision correlations between classifiers.

For correlated decisions, the ideal error rates calculated using the equations (1 & 2) under independence assumption are different from experimentally observed error rates or those predicted after applying correlation values in equation 3. The correlation coefficients from equation (4) are used as a measure to determine the dependence relationship. This relationship results in lower/higher error rates than the ideal case. The 2nd order coefficient has strong positive and negative dependence with error difference in FRR and FAR respectively [10]. For higher order coefficients, the determination of dependence relationship is complex as *n*th order correlation coefficient is dependent on the relative weight of 2nd, 3rd . . , (*n* − 1)th order coefficients.

One sufficient condition for determining the favourable dependence between '*n*' client decisions is the positive even-order correlation coefficients and negative-odd order correlation coefficients [8]. Similar analysis has shown that negative even-order correlation coefficients and positive odd-order correlation coefficients are favourable for '*n*' impostor decisions [8]. Since the even/odd order coefficients related to combination of '*n*' instances may not be of the same sign, the above analysis based on correlation signs, in general, can be misleading. Further, it is possible that lower order coefficients with unfavourable dependence when combined can result in higher order coefficients with favourable dependence. Therefore, sign and magnitude of the correlation coefficient are required to determine the absolute solution for dependence of the decisions.

2.1. Favourable Dependence of '*n*' instances for Impostor decisions

The predicted false acceptance rate (FAR) for correlated decisions is lower than the errors calculated under independence assumption for the fusion rule. The dependence between the impostor decisions can be considered favourable when the correlation factor in equation (3) is negative, i.e.,

$$\left(\sum_{i<j}\gamma^0_{ij} z^0_i z^0_j + \sum_{i<j<k}\gamma^0_{ijk} z^0_i z^0_j z^0_k + ...\right) < 0 \quad (6)$$

When FAR for each of '*n*' instances is considered to be equal to α, the inequality for favourable dependence can be expressed using correlation coefficients and FAR 'α'. For *n*=2, equation (6) can be reduced to

$$\gamma^0_{12}\ \left(\frac{1-\alpha}{\alpha}\right) < 0 \quad (7)$$

Since $\alpha \le 1$, the error factor is either zero or positive (undefined value when $\alpha = 0$). Thus, dependence between two decisions is favourable when correlation is negative, i.e., $\gamma^0_{12} < 0$. For *n*=3, the favourable dependence is determined using the inequality

$$\left(\gamma^0_{12} + \gamma^0_{13} + \gamma^0_{23} + \gamma^0_{123}\sqrt{\frac{1-\alpha}{\alpha}}\right) < 0 \quad (8)$$

When the 2nd and 3rd order correlation coefficients are of same sign and positive, the inequality (8) is not satisfied and therefore the impostor decisions are considered to be unfavorably dependent. If the 2nd and 3rd order correlation coefficients are of same negative sign, the dependence between client decisions is considered to be favourable. For positive 2nd order coefficients and negative 3rd order coefficient, the decisions are favourable when sum of 2nd order coefficients is less than the product of the 3rd order correlation and the error factor $\left(\gamma^0_{123}\sqrt{(1-\alpha)/\alpha}\right)$. Although positive 2nd order coefficients are unfavourable (equation 5) for two instance fusion, the use of these coefficients can result in favourable dependence between the decisions of three instances. When 2nd (even) order coefficients are negative and 3rd (odd) order coefficients are positive, the decisions are supposed to be favourable [8]. But this analysis based on signs may not be reliable for all values of correlation, i.e., when sum of the 2nd order coefficients is less than the product of the 3rd order correlation and error factor.

Therefore, a generalized equation for determining the favourable dependence between impostor decisions of '*n*' instances is developed and can be given as

$$\left(\sum_{i<j} \gamma_{ij}^{0} + \sum_{i<j<k} \gamma_{ijk}^{0} \left(\frac{1-\alpha}{\alpha} \right)^{\frac{1}{2}} + .. + \gamma_{1..n}^{0} \left(\frac{1-\alpha}{\alpha} \right)^{\frac{n-2}{2}} \right) < 0 \quad (9)$$

From the above equation, it is evident that the 2nd-nth order correlation coefficients of the same negative sign are favourable whereas coefficients with same positive signs are unfavourable. When the coefficients are of different signs, the dependence between the decisions is determined using the base FAR and magnitude of the correlation coefficients.

2.2. Favourable Dependence of '*n*' instances for Client decisions

The favourable dependence for multi-instance fusion of client decisions is analyzed in steps similar to fusion of impostor decisions. The generalized equation for favourable dependence of client decisions from '*n*' instances with equal FRR of 'ρ' is given as

$$\left(\sum_{i<j} \gamma_{ij}^{1} + \sum_{i<j<k} \gamma_{ijk}^{1} \left(\frac{\rho}{1-\rho} \right)^{\frac{1}{2}} + .. + \gamma_{123..n}^{1} \left(\frac{\rho}{1-\rho} \right)^{\frac{n-2}{2}} \right) > 0 \quad (10)$$

From the above equation, it is evident that the 2nd-nth order correlation coefficients of same sign are favourable when positive and unfavourable when negative. If the coefficients are of different signs, the dependence between the decisions is determined using the base FRR and magnitude of correlation between client decisions. The best set of digit combinations with favourable dependence for client decisions, impostor decisions or both can be determined using the equations (9) & (10).

3. FUSION OF CORRELATED DECISIONS FROM MULTIPLE SAMPLES

The decisions from multiple samples can be combined in the fusion process in order to obtain a reliable decision at an instance level. The BLE (equation 3) is also applicable for the prediction of error rates for multi-sample 'OR' fusion *with incorporation of correlation* between the decisions [11]. The correlation coefficients between '*m*' client samples (γ^1) and impostor samples (γ^0) are calculated using the equation (4). The ideal error rates for the 'OR' fusion of multiple samples [9] are

$$p_I^0 = \delta_1 \delta_2 \delta_3 ... \delta_m \quad \left(\delta_i = \left(1 - FAR_i\right) \text{for } i^{th} \text{ sample} \right) \qquad (11)$$

$$\rho_I^1 = \rho_1 \rho_2 \rho_3 ... \rho_m \quad \left(\rho_i = FRR_i \text{ for } i^{th} \text{ sample} \right) \qquad (12)$$

The favourable dependence between two correlated decisions, combined using 'OR' rule, can be achieved when the 2nd order client correlation coefficients are negative and 2nd order impostor coefficients are positive [7, 10]. As with the case with multi-instance 'AND' fusion, the *m*th order correlation coefficient for repeated samples is dependent on 2nd, 3rd . . . , (m − 1)th order coefficients and so the relationship between *m*th order correlation coefficients and error differences for clients and impostors is weak.

The 'AND' fusion rule, used for multiple instances, is the complement of the 'OR' fusion rule, used for multiple samples. Analysis similar to the 'AND' rule can be carried out to find the favourable dependence to the 'OR' rule. Analysis on client decisions for the OR rule is similar to the analysis on impostor decisions for the AND rule. Thus the generalized equation for favourable dependence between client decisions fused using 'OR' rule is the same as equation (9) in which the error rates and correlation coefficients for impostors are replaced with that of client values, i.e., $\alpha \,\&\, \gamma^0$ are replaced with $\rho \,\&\, \gamma^1$ respectively. Similarly, the generalized equation for favourable dependence between impostor decisions combined using 'OR' rule is the same as equation (10) in which $\rho \,\&\, \gamma^1$ are replaced with $\alpha \,\&\, \gamma^0$ respectively. These equations enables to determine particular instance with favourable dependence for either client samples, impostor samples or client and impostor samples.

4. FUSION OF CORRELATED DECISIONS FROM MULTIPLE INSTANCES AND MULTIPLE SAMPLES

A fused classifier architecture based on sequential integration of multi-instance and multi-sample fusion schemes allows controlled trade-off between false alarms and false rejects when the decisions are considered to be statistically independent [9]. For an individual to be declared genuine for a particular instance, it is considered sufficient if any one sample presented to the system gets accepted. Acceptance decisions are logical 'OR' for multiple samples. The individual is considered to be an impostor when all the 'm' samples are rejected. Rejection decisions are logical 'AND' for multiple samples. Conversely, it is considered necessary in the sequential decision framework that an individual be accepted by all instances in the sequence of decision stages. Acceptance is thus logical 'AND' for multiple instances. If the individual is rejected by any decision stage, the sequence terminates and thus rejection decisions are logical 'OR' for multiple instances.

$$\alpha_{S1,S2,..Sm}^{Cn} = 1 - \left(\left(1-\alpha_{S1}^{Cn}\right)....\left(1-\alpha_{Sm}^{Cn}\right)\right)\left(1 + \sum_{i<j}\gamma_{ij}^{0}\sqrt{\frac{\alpha_{S1}^{Cn}\alpha_{S2}^{Cn}}{\left(1-\alpha_{S1}^{Cn}\right)\left(1-\alpha_{S2}^{Cn}\right)}} + \sum_{i<j<k}\gamma_{ijk}^{0}\sqrt{\frac{\alpha_{S1}^{Cn}\alpha_{S2}^{Cn}\alpha_{S3}^{Cn}}{\left(1-\alpha_{S1}^{Cn}\right)\left(1-\alpha_{S2}^{Cn}\right)\left(1-\alpha_{S3}^{Cn}\right)}} + ..\right) \quad (13)$$

$$\left(\sum_{i<j}\gamma_{ij}^{0}\prod_{k=1}^{n}\prod_{k\neq i,k\neq j}\left(\sqrt{\frac{\alpha_{S1,S2,..Sm}^{Ck}}{1-\alpha_{S1,S2,..Sm}^{Ck}}}\right) + \sum_{i<j<k}\gamma_{ijk}^{0}\prod_{l=1}^{n}\prod_{l\neq i,l\neq j,l\neq k}\left(\sqrt{\frac{\alpha_{S1,S2,..Sm}^{Cl}}{1-\alpha_{S1,S2,..Sm}^{Cl}}}\right) + ... + \gamma_{123...n}^{0}\right) < 0 \quad (14)$$

The fusion performance of the proposed architecture is evaluated for the incorporation of correlation between the decisions [10]. But the actual conditions for determining the favourable dependence are not explained in detail. As the decision correlation for the combination of multiple instances with single sample (section 2) and multiple samples can be different, it is significant to determine the combinations with favourable dependence for improved proposed fusion performance.

The false acceptance rate, $\alpha_{S1,S2,...Sm}^{Cn}$, for the fusion of '*m*' samples (*S1, S2,... Sm*) for an '*n*th' instance can be obtained using the equation (13). The claim is declared genuine, at the end of '*n*' instances, if accepted at all the instances ('AND' rule). Considering $\alpha_{S1,S2,..Sm}^{Ci}(i=1,2,3...n)$ to be the individual FARs for '*n*' instances with '*m*' samples, the expression (14) for favourable dependence can be developed similar to fusion of multi-instance fusion (eq. 9). The fusion of '*m*' samples and '*n*' instances, thus, depends on the base performances, correlation coefficients between the repeated samples and correlation between the instances being combined. Due to complex relationship between these terms and non-linearity of multiple correlation coefficients, the solution is not direct and intractable.

The favourable dependence between client decisions can be analysed in steps similar to that of impostor decisions. The false rejects for the fusion of '*m*' repeated samples can be expressed using equation (15). If the individual is rejected at any instance, the client claim can be rejected. The false rejects for the fusion of '*n*' multiple instances can thus be determined using the 'OR' logic. The generalised inequality for determining the favourable dependence with individual FRR $\rho_{S1,S2,..Sm}^{Ci}(i=1,2,3...n)$ for '*n*' instances with '*m*' samples is expressed in equation (16). When the 2nd-nth order impostor correlation coefficients are of same sign and negative, the dependence is favourable (eq. 14) whereas positive 2nd-nth correlation coefficients are favourable on client decisions. For correlation coefficients with different signs, favourable dependence can be determined between the samples for each instance and base error rates of the instances. The above analysis of favourable dependence for the proposed fusion enables to find instance combinations with experimental/predicted error rates smaller than ideal error rates.

5. EXPERIMENTAL SETUP

Speech data from the CSLU Speaker Recognition Version 1.1 database is used for evaluating performance of the proposed fusion scheme. The data comprise of spoken digit strings that are manually segmented into individual digits. The methodology used is the same as explained in [9]. Mel Frequency Cepstral Coefficient features are extracted by processing utterances in 26 ms different training sets (21 client utterances) are first chosen for creating speaker specific digit dependent HMM models. Once the models are trained, the remaining data is divided into four different tune and test data subset combinations. Each tune set (35 client and 140 impostor utterances) is used to set appropriate digit dependent threshold, evaluate individual classifier error rates and the test set (70 client and 420 impostor utterances) is used to evaluate the performance of the proposed fusion. The evaluation is presented using the pooled results for tests performed on 11 speakers.

In text-dependent speaker verification (TDSV) mode, the digit is known and the speaker is unknown. If the claimed speaker's model for the digit matches the utterance, it is accepted. This may be a true or false acceptance depending on whether the utterance came the claimed speaker or an impostor. Impostor testing is done using utterances of the same (known) digit, resulting in true rejections or false acceptances. An instance in the context of TDSV by the proposed architecture refers to the digits which form the decision stages. A sample represents any single utterance of a digit from a speaker. Physically favourable dependence of classifiers in this context would imply that if one instance/digit is likely to be in error owing to a particular type of degradation,

$$\rho_{S1,S2,...,Sm}^{Cn} = \rho_{S1}^{Cn}\rho_{S2}^{Cn}...\rho_{Sm}^{Cn}\left(1 + \sum_{S1<S2}\gamma_{S1S2}^{1}\sqrt{\frac{\left(1-\rho_{S1}^{C1}\right)\left(1-\rho_{S2}^{C1}\right)}{\rho_{S1}^{Cn}\ \rho_{S2}^{Cn}}} + \sum_{S1<S2<S3}\gamma_{S1S2S3}^{1}\sqrt{\frac{\left(1-\rho_{S1}^{C1}\right)\left(1-\rho_{S2}^{C1}\right)\left(1-\rho_{S3}^{C1}\right)}{\rho_{S1}^{Cn}\ \rho_{S2}^{Cn}\ \rho_{S3}^{Cn}}} + ..\right) \quad (15)$$

$$\left(\sum_{i<j}\gamma_{ij}^{1}\prod_{k=1}^{n}\prod_{k\neq i,k\neq j}\left(\sqrt{\frac{1-\rho_{S1,S2,..Sm}^{Ck}}{\rho_{S1,S2,..Sm}^{Ck}}}\right) + \sum_{i<j<k}\gamma_{ijk}^{1}\prod_{l=1}^{n}\prod_{l\neq i,l\neq j,l\neq k}\left(\sqrt{\frac{1-\rho_{S1,S2,..Sm}^{Cl}}{\rho_{S1,S2,..Sm}^{Cl}}}\right) + .. + \gamma_{123...n}^{1}\right) > 0 \quad (16)$$

another instance/digit is simultaneously likely to be correct more of the time. Although it is rather unexpected behavior, it is possible in scenarios where a faster rate of speech than used for training one digit may result in error but the increased rate may be closer to training conditions for another digit. The same applies to increased noise, which may take the input away from the model for one instance/digit and towards the model for another depending on what the prior training conditions.

6. EMPIRICAL EVALUATION

The equations developed in section 2 and section 3 are used to determine the combinations with favourable dependence between decisions from multiple instances and multiple samples. The error rates (FRR & FAR) for multi-instance and multi-sample fusion schemes with favourable combinations are presented in figure 1(a) and 1(b) respectively. The multi-instance fusion performance is better when impostor and client-impostor favourable digit combinations are considered as FAR decreases with increase in digits. On the other hand client and client-impostor favourable digits have shown improved performance as FRR decreases with multiple samples. This dependence on client and/or impostor decisions can be varied with integration of instances and samples. Table 1 presents the ideal error rates (integration of equations 1-11, 2-12) and experimental/predicted error rates (using 2nd-5th order correlation coefficients) for the sequential fusion of instances with multiple samples. The ideal FRRs are higher than the experimental FRRs whereas the ideal FARs are lower than experimental FARs for proposed fusion. This *error difference* (i.e., difference in ideal and experimental error rates) and correlation between decisions decreases with increase in digits and samples used for fusion. Though the differences in performance for fusion of independent and dependent decisions decreases with increase in digits and samples used in a combination, the effect of favourable dependence on fusion performance is to be investigated.

The mean total error rates (TER) for digit combinations that are favourable for client, impostor and client-impostor decisions are shown in figure 2. The TER, in general, increases for digit combinations with single sample (fig. 2(a)) and decreases with increase in samples used for fusion. Improved fusion performance using client favourable combinations can be achieved with increase in samples. For impostor favourable combinations, the performance improvement can be

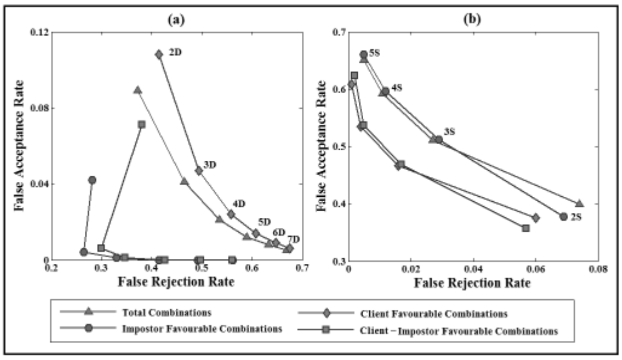

Figure 1 Verification Error Rates for combinations with favourable dependence for (a) Multi-Instance Fusion and (b) Multi-Sample Fusion

decrease in FRR for multiple samples. Performance improvement can be achieved, for this dataset, irrespective of the samples and instances, if client-impostor favourable combinations are used for speaker verification. For example, the TER of 20.2% for fusion of seven digits with 5 samples can be reduced to 12.6% and 11.9% when the digit combinations used are favourable for client decisions and impostor decisions respectively. The error rate can be further reduced to 2.1%, if verification is based on digit combinations that are favourable for both client and impostor decisions.

The client-impostor favourable combinations also ensure that the *experimental or predicted error rates* (fusion of favourable dependent decisions) are always lower than the *ideal error rates* (fusion of independent decisions). For example, the fusion for (5, 5) has TER of 10.7% for favourable client-impostor combinations which is lower than 25.8% and 26.4% for ideal (fusion of independent decisions) and experimental (fusion of dependent decisions that are favourable and unfavourable) errors shown in table 1 respectively. These client-impostor favourable digit combinations can be different between speakers but are similar for a speaker across different datasets. For example, the digits in sequence 2-9-1-3-7, i.e., the combinations 29, 291, 2913, 29137 are favourable for spkr-0047 whereas the sequence 2-3-1-4-7 is favourable for spkr-0241 across datasets. But the sequence 2-5-3-4-7 which is unfavourable for spkr-0047 is observed to be favourable for spkr-0241. Therefore the use of speaker-specific digit combination can be considered as another measure to ensure reliable identity verification. In real world applications, the favourable combinations specific for an individual can be pre-determined on the development set and later used in

Table 1 Ideal and Experimental Error Rates with 2nd-5th Order Client and Impostor Correlation Coefficients

(n, m) = number of (*instances*, *samples*)	Ideal Error Rates		Experimental Error Rates		Correlation Coefficients	
	FRR	FAR	FRR	FAR	Client	Impostor
(1, 1)	$0.237^{\pm0.14}$	$0.238^{\pm0.14}$	$0.237^{\pm0.14}$	$0.237^{\pm0.14}$	-	-
(2, 2)	$0.140^{\pm0.12}$	$0.190^{\pm0.16}$	$0.136^{\pm0.12}$	$0.200^{\pm0.16}$	$0.051^{\pm0.15}$	$0.052^{\pm0.07}$
(3, 3)	$0.077^{\pm0.07}$	$0.193^{\pm0.18}$	$0.076^{\pm0.07}$	$0.203^{\pm0.18}$	$0.001^{\pm0.18}$	$0.005^{\pm0.05}$
(4, 4)	$0.044^{\pm0.04}$	$0.211^{\pm0.21}$	$0.043^{\pm0.04}$	$0.219^{\pm0.21}$	$0.001^{\pm0.04}$	$0.001^{\pm0.05}$
(5, 5)	$0.023^{\pm0.02}$	$0.235^{\pm0.23}$	$0.023^{\pm0.02}$	$0.241^{\pm0.24}$	$-0.001^{\pm0.001}$	$-0.001^{\pm0.05}$

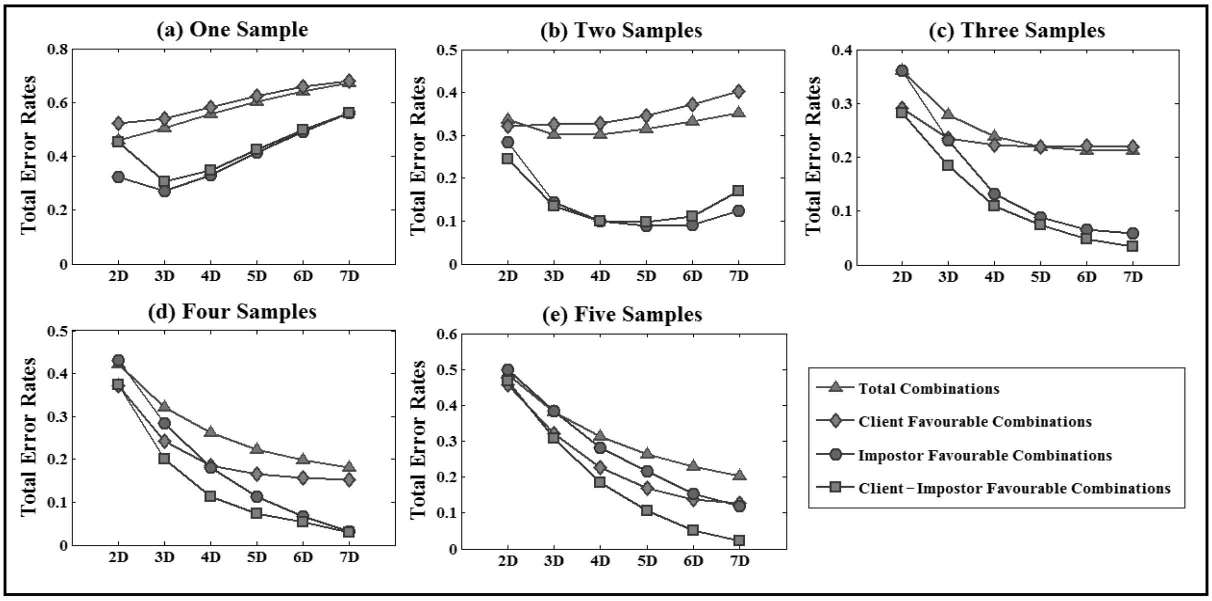

Figure 2 Total Error Rates for the Proposed Fusion with Favourable Client, Impostor and Client-Impostor Combinations

speaker testing. This method of evaluation ensures that the predicted fusion parameters, i.e., the number of digits and samples or correlation values [10], used for verification always produce a reliable final decision and with errors lower than that of errors estimated with ideal condition of statistical independence between decisions.

7. CONCLUSION

Statistical dependence between two classifier decisions is theoretically shown to improve the performance over statistically independent decisions. However, the analysis for '*n*' classifiers is complex because of the dependence of nth order correlation on lower order coefficients. Expressions are developed for satisfying conditions of favourable dependence using correlation and base performance of instances and/or samples used for fusion. The performance improvement is demonstrated for fusion of '*n*' favourable dependent (client, impostor, client-impostor) decisions over '*n*' independent decisions. The sequential fusion of favourable decisions with multiple samples is shown to better control the trade-off between false accepts and false rejects. As the expression are developed for the proposed fusion using 'AND' and 'OR' fusion rules, and thus the analysis is applicable to other biometric modalities suitable for remote authentication.

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